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Hell and high water: Precipitation shocks and conflict violence in the Philippines

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1. Introduction

As climate change destabilizes global weather patterns, concern is rising over the potential risks these changes might pose to peace and stability in developing states. A vigorous research program has emerged to address the relationship between climate change and civil conflict, with two special issues of *Political Geography* (2007, 2014) devoted to the subject. A common expectation is that if conflict and violence are to proliferate, then precipitation shocks—droughts, floods, and storms—are likely to be key causal factors. Scholars anticipate these events to influence political violence via their effects on subsistence resource accessibility and livelihood opportunities in vulnerable states. Despite a growing number of studies examining these phenomena, robust conclusions and isolation of clear causal processes remain elusive (Bernauer, Böhmelt, & Koubi, 2012; Buhaug, 2015; Salehyan, 2014). Researchers have found precipitation shocks to be positively (Raleigh & Kniveton, 2012) and negatively (Salehyan & Hendrix, 2014) associated with conflict violence, as well as to demonstrate minimal correlation (Slettebak, 2012; Theisen, Holtermann, & Buhaug, 2011/12). This “cacophony of findings” has led to calls for future studies to incorporate greater specificity and context in research design and hypothesis testing to determine if, when, and under what conditions climatic processes generate conflict or some other social outcome (Buhaug, 2015; Salehyan, 2014; Seter, 2016).

Accordingly, this study draws on a unique micro-level dataset of armed intra-state conflict in the Philippines, 2001–2007, to analyze the impact of precipitation shocks on the incidence and severity of the country's four largest and longest running civil wars, those waged by insurgent groups: the Communist Party of the Philippines-New People's Army (CPP-NPA), Moro National Liberation Front (MNLF), Moro Islamic Liberation Front (MILF), and Abu Sayyaff Group (ASG) against the Armed Forces of the Philippines (AFP). In doing so, this study contributes to the literature in several ways: First, while the bulk of existing quantitative analyses of climate and conflict assess the risks precipitation shocks pose to conflict onset or to low-level political violence, this study takes conflict as a starting point and examines the impacts these phenomena can have on its incidence and severity. This distinction is important because many of the world's most protracted and violent conflicts occur in states that are also among the most vulnerable to environmental shock (Eastin, 2016). Thus, analyzing these linkages also has the potential to build insight into conflict intractability. Additionally, isolating causal drivers of conflict escalation is important because the factors that explain why conflicts begin do not necessarily correspond to those that explain their internal dynamics (Lacina, 2006). Second, while the majority of studies evaluating conflict violence incorporate pooled conflict data, this study draws on actor-disaggregated data that identify the agents—insurgents or state military forces—who initiate each attack and who experience each battle death or casualty. The utility of this approach arises from the ability to parse whether climate variability influences the behavior of state military forces and insurgent groups in distinct ways. This approach can also corroborate causal arguments regarding the identity of those agents waging violence, and address whether climatic variability renders a net positive or negative impact on the capabilities of distinct combatant group types. Finally, this study draws data from the Philippines, a tropical agrarian country among the world's most vulnerable to climate change and also among its most conflict-prone, and thus provides an opportunity to examine the implications of precipitation shocks on conflict dynamics in an intrinsically

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important case.

The results of this study indicate that precipitation shocks in the Philippines correspond with significant escalations in conflict violence across the four major insurgencies fought from 2001 to 2007. Years that are wetter and drier than average, and years with relatively greater typhoon destruction are all associated with increases in incidents, battle deaths, and casualties in civil conflict. While these increases apply to insurgent groups, they are not confined to them. Surprisingly, climatic variability appears to heighten the pace of governmental attacks on insurgents even more so than reverse: a one standard deviation increase in mean precipitation levels in a given province/year is associated with a 35% rise in insurgent attacks against governmental forces and a 43% rise in governmental attacks on insurgent groups.

What explains these dynamics? I argue that they result from the positive impact precipitation shocks can have on the capabilities of combatant groups to recruit and generate support from affected populations, and the tactical advantages they create for each side in engaging with the opposition. First, precipitation shocks can facilitate insurgent recruitment when their impact on resource accessibility and livelihoods diminish the opportunity costs of conflict participation, increase costs of non-participation, and heighten anti-state grievances. Local governmental responses to environmental crises can aggravate these effects when politics guides resource allocation. In the Philippines, the structure of the institutions charged with disaster management at the local level provides considerable opportunities for chief executives of local government units (LGUs) to engage in graft and malfeasance with disaster mitigation and relief resources. Doing so can intensify victims' political and economic marginalization, heighten vulnerability, and substantiate insurgents' anti-state rhetoric. The impact of these efforts can increase recruitment and bolster public support, which heightens group capabilities to fight. Second, factors similar to those that enhance insurgent capabilities following a precipitation shock can also apply to the state. Livelihood crises afford military forces with opportunities to increase conscription in paramilitary and self-defense force units in contested regions. In the Philippines, these brigades, “Civilian Armed Forces Geographical Units” (CAFGUs), act as local reserve forces that perform counterinsurgency operations and aid in defense of members' home communities. For those whom military service is a viable option, the guarantee of a steady paycheck and other benefits can offset livelihood losses resulting from an environmental calamity. Moreover, the military's role in distributing relief supplies and providing security escorts to humanitarian agencies can legitimize military presence in conflict zones, facilitate trust-building in local communities, and enhance intelligence gathering, the impact of which can assist counterinsurgency efforts. Taken together, the overall outcome of these dynamics should exert a positive effect on the capabilities of insurgent groups and state forces to engage with one another on the battlefield, which should amplify the frequency and lethality of conflict violence.

2. Climate variability, scarcity, and violence in civil conflict

Research into the climate/conflict nexus has increased in recent years, both as climate change continues apace, and as improvements in data collection enable more robust hypothesis testing. A central theme in many of these works concerns the impact that resource scarcity has on the likelihood that affected actors will initiate violence against the state or other non-state groups (Landis, 2014; Miguel, Satyanath, & Sergenti, 2004). The expectation is that as rising climatic variability undermines economic opportunities and food and water accessibility, the opportunity costs of conflict decline and grievances can emerge that can encourage collective violence. These effects should be pervasive in states that depend on agricultural production for subsistence and livelihoods, because this sector is among the most vulnerable to shock. The result is expected to reduce the value of and access to environmental resources, which can restrict income-generation, magnify chronic poverty, inequality and marginalization, and foster migration and displacement. When the state is unwilling or unable to respond, conflict and violence can proliferate.

A potential flaw in this argument suggests that although resource scarcity might increase individuals' willingness to fight, it can also decrease their capabilities to organize and initiate collective action. Conflict is costly; it requires a critical mass of popular support and access to resources sufficient to attract, supply, and feed members. When environmental phenomena undermine a group's ability to meet these challenges, the likelihood of conflict can decline. Landis (2014), for example, finds that conflict onset in countries with high seasonality is more likely during times of warm weather, as extended growing seasons increase the availability of food resources, and as warmer temperatures can facilitate troop mobilization. Though Landis examines temperature, we might anticipate similar outcomes to result from stable and predictable precipitation patterns.

While scarcity and livelihood crises might inhibit conflict onset, variations in the temporal dynamics of ongoing wars do not necessarily face the same barriers to collective action (Lacina, 2006). Consequently, scholars have begun to examine the environmental determinants of violence within conflicts as a means of gauging emerging security threats (Caruso, Petrarca, Banca, & Ricciuti, 2016; Raleigh & Kniveton, 2012; Salehyan & Hendrix, 2014). For insurgents, factors influencing capabilities to wage violence include groups' recruitment capabilities and levels of organization and armament, as well as the individual-level motives and incentives necessary to sustain violent campaigns (Lacina, 2006; Weinstein, 2007). For the state, a motivated military force with access to political and material resources sufficient to execute and support combat operations is paramount. For both, the capability to penetrate non-combatant populations in contested territory to draw material support and gather intelligence can offer tactical advantages that can facilitate attacks and amplify casualties (Berman, Shapiro, & Felter, 2011; Condra & Shapiro, 2012).

Prior scholarship contests the effect that environmental processes should have on these dynamics. On the one hand, some find that scarcity-induced livelihood crises can act as threat multipliers that exacerbate conflict violence (Maystadt & Ecker, 2014). Wischnath and Buhaug (2014) find that decreases in agricultural production, which can be a consequence of climatic shock, correspond to increases in state-based political violence in India. They argue decreased opportunity costs of conflict, increased insurgent recruitment, and heightened anti-state grievances result from increases in food and economic insecurity. Because each of these processes should enhance conflict participation, and because participation bolsters the capabilities of insurgent groups to fight, conflict escalation should follow. While these authors employ data on food production to test this thesis, others have yielded similar outcomes with climatic data. Caruso et al. (2016) find that the negative effects of increases in the average minimum temperature on rice yields during the growing season can elevate the incidence of anti-state and inter-group violence, terrorist attacks, and lynching. Raleigh and Kniveton (2012) examine deviations from average precipitation levels in East Africa, finding that anti-state and communal conflict incidents rise in times of both excess and scarce rainfall. They argue that this finding represents evidence for both the “scarcity breeds resource competition” hypothesis, and a narrative that suggests increasing resource availability, an outcome expected to occur as a result of

excess precipitation, foments rent-seeking behavior that motivates conflict participation.

On the other hand, an alternative view suggests that environmentally induced livelihood shocks should diminish, rather than multiply conflict threats, because the same crises that can provoke individuals to participate in conflict can also undermine the capabilities of combatant groups to fight. Salehyan and Hendrix (2014), argue that because armed groups tend to rely on civilian populations for food, shelter, and financing in the form of revolutionary taxation, phenomena that reduce resource access can also limit groups' ability to feed and pay fighters, and to attract the recruits necessary to sustain combat. Moreover, an individual's willingness to join a war effort should also decline, because the need to ensure basic subsistence requirements can diminish time available to devote to subversive activities. These authors' findings suggest that conflict violence declines during periods of below average rainfall when scarcities limit insurgent capabilities, and rises in wetter years when excess precipitation creates a more favorable tactical environment for insurgents to wage attacks, and when increases in crop availability enable insurgent groups to build organizational strength. Additional studies have generated theoretical insights and empirical findings consistent with this line of reasoning (Theisen, 2012; Witsenburg & Adano, 2009).

In part, discrepancies extant in prior literature reflect contextual variations across (or even within) studies that decrease case comparability. This situation characterizes the agricultural effects of climatic variability, because different types of shocks can hold distinct implications for agricultural productivity in particular locations. (Buhaug, 2015; Seter, 2016). For example, the discovery of a positive association between above average rainfall and conflict violence has previously been taken to indicate that greater crop availability can facilitate violent mobilization (Raleigh & Kniveton, 2012; Salehyan & Hendrix, 2014). While this relationship might hold for locations such as the drylands of Sahelian and Sub-Saharan Africa (Buhaug, Benjaminsen, Sjaastad, & Theisen, 2015; Hatibu, Mahoo, & Gowing, 2000), its applicability across contexts is less clear (Wilkie, Morelli, Rotberg, & Shaw, 1999). In regions where rice production predominates, excess precipitation can be problematic because prolonged submersion diminishes yields (Kotera, Nguyen, Sakamoto, Iizumi, & Yokozawa, 2014; Rosenzweiga, Tubiello, Goldberg, Mills, & Bloomfield, 2002). A surplus of rainfall during the growing season can deplete oxygen, leach nutrients from the soil, encourage bacterial and fungal growth, and create ideal conditions for the emergence of rodent infestations that wreak havoc on production (Alam et al., 2011; Mendoza, 2009; Rosenzweiga et al., 2002). When heavy rainfall occurs immediately prior to harvesting, significant crop losses can result (Lansigan et al., 2000). Flooding from typhoons and bouts of heavy rainfall can wash away fields and exacerbate erosion. Because of high soil instability, upland areas, which are often inhabited by marginalized populations, are among the most vulnerable to these effects. The danger to rice production from excess rainfall has been significant enough to motivate the International Rice Research Institute to prioritize the development and distribution of flood-resistant strains of rice in South and Southeast Asia (IRRI, 2012).

Rather than assuming that excess precipitation necessarily generates an abundance of resources, a safer bet would be that greater stability and predictability in regional weather patterns can result in more productive agricultural yields (Ray, Gerber, MacDonald, & West, 2015). In this study, I expect more favorable yields to occur in years that experience precipitation totals hewing closer to long-term averages, while deviations from these patterns are more likely to diminish productivity. I test the impact of precipitation shocks with data that measures mean rainfall deviations, as well as to incorporate data on the incidence and magnitude of typhoon storms and rain-fed rice production.

An additional factor complicating the interpretability and comparability of prior studies concerns a failure to specify agency in the production of conflict violence, especially for state military forces (Buhaug, 2015). For analyses of communal conflicts or low-level political violence, this omission might be justified. For conflicts where the military is an active participant, as it is in most revolutionary and separatist wars, assuming or omitting its role can obscure the identification of causal processes. For example, a study might find a positive relationship between a precipitation shock and the incidence of violence, but without accounting for the identity of those responsible, it would be unclear whether this effect resulted from increased insurgent capabilities and opportunities to wage conflict, increased state repression of insurgent groups, or both. In this study, I attempt to correct for this bias by incorporating data that measures the identity of the agents of violence in conflict (insurgents or the state), as well those who experience its effects.

3. Precipitation shocks and conflict violence in the Philippines

Precipitation shocks can increase the likelihood that individuals will participate in conflict, and bolster the capabilities of armed groups to mobilize them. When droughts, floods, and storms reduce subsistence resource access and livelihood opportunities in agricultural sectors, the relative value of selective incentives for joining or supporting an armed group should increase, and the opportunity costs of participation should decline (Barnett & Adger, 2007; Lichbach, 1995). The outcome can bolster the ranks of armed groups, and increase their capacity to wage violence. The impact of precipitation shocks can also increase the costs of abstaining from conflict when they decrease an individual's ability to protect themselves and their family from wartime violence. Kalyvas and Kocher (2007) demonstrate that conflict abstention can be costly when the threat of victimization through indiscriminate violence or erroneous targeting looms large. Precipitation shocks can increase exposure to conflict processes and environmental hazards, which can magnify these effects (Barnett & Adger, 2007). During a livelihood crisis, groups can conscript victims or prevent them from accessing resources necessary for survival, both of which can necessitate conflict participation (See: Heilprin, 2011; for example).

Rising scarcity and lost livelihoods can also motivate individuals to join a conflict when environmental disasters exacerbate political grievances. Armed groups can capitalize on this situation through propaganda campaigns aimed at strategically framing the causes and consequences of humanitarian crises to suit their political purposes (Birkland, 1998). In the Philippines, the CPP-NPA has adopted this tactic to generate support for their movement. Cadres often assist in providing reconstruction support in rural barrios following destructive typhoons. They use these occasions as opportunities to hold indoctrination seminars for the purpose of motivating villagers to join the movement, and for encouraging reciprocal behavior—providing food, shelter, resources, or support to NPA fighters—in the future (Author interview 2011). The National Democratic Front of the Philippines (NDFP), the group's political wing, abets these efforts through the use of Internet and social media to distribute propaganda connecting disasters to governmental mismanagement (See for example: del Pueblo, 2004). These actions resonate with the public because the politics surrounding disaster management in the Philippines is perceived to be rife with corruption, especially at the local level (Bankoff, 2003). The structure of institutions responsible for emergency preparedness and response, the

National (and Local) Disaster Coordinating Councils, provides LGU chief executives considerable leeway to appropriate relief and rehabilitation resources for personal gain.[1] Graft and the distribution of humanitarian assistance according to political patronage enable these elites to consolidate power at the expense of the most marginalized and vulnerable, a practice Bankoff (2003) describes as "… symptomatic of a [corrupt political] culture that permeates all levels of the public service down to relief workers at the disaster site and the voluntary labors of NGOs, though the scale in these latter cases is often petty." (100). The result exacerbates preexisting social and economic inequalities and bolsters anti-state rhetoric, which in turn can increase public support for insurgent groups and facilitate their recruitment.

Heightened support and recruitment can escalate violence in civil conflict (Lacina, 2006; Weinstein, 2007). There are at least four reasons for this: First, recruitment fortifies armed group ranks. The more soldiers there are, the more that can participate and die on the battlefield. Second, civilian supporters can provide intelligence information that can facilitate successful attacks and counterattacks. Third, larger and more prolific insurgencies pose a proportionately larger threat to state security, and are more likely to initiate countermobilization from incumbent forces. Finally, a community's support for a particular armed group can act as a signal that can motivate opponent attacks, especially in areas of incomplete territorial control (Hirose, Imai, & Lyall, 2014). Because individuals' attitudes can foreshadow their behavior, community signaling of combatant preferences can streamline opponents' target selections.

For insurgents, an additional tactical advantage can arise when non-combat humanitarian duties increase military vulnerability to attack. Because in the Philippines, the military is the primary institution responsible for providing humanitarian assistance, an environmental calamity in a contested region can create opportunities for insurgents to ambush relief convoys, appropriate supplies, and diminish military ranks. Wrecked infrastructure can increase military vulnerability to these attacks because military forces rely to a greater extent than do insurgents on mechanized battle implements such as tanks and convoys for troop transport. While the precise contribution of these actions to the overall level of conflict violence is unclear, anecdotal evidence suggests attacks are not uncommon (dela Cruz, 2015; Walch, 2014).

Taken together, the combination of recruitment and tactical opportunities that precipitation shocks create for insurgents provide the theoretical basis for Hypothesis one (H1).

H1. Precipitation shocks increase insurgent violence against governmental forces.

While studies often associate these dynamics with insurgency, similar processes might also enable state military forces to enhance civilian support and recruitment. In the Philippines, material incentives arising from lost livelihoods have likely increased civilian participation in Civilian Armed Force Geographical Units (CAFGUs), paramilitary brigades created to assist the Armed Forces of the Philippines (AFP) in countering rising insurgent threats in the countryside. As of 2015, approximately 53,000 soldiers comprised CAFGU brigades scattered across fourteen battalions of the Army (Acosta, 2015). These groups act as reserve forces for and operate under the command of the AFP, are issued military firearms, and engage in regular patrols. They also take part in military operations alongside regular AFP forces, and assist military personnel in delivering humanitarian assistance. For potential recruits, the promise of a regular paycheck—as of 2015, pay totaled around \$100/month—educational programs, medical assistance and insurance access, should motivate membership, particularly for those living in rural and impoverished locales (Acosta, 2015). A livelihood crisis should heighten these motives, and increase the AFP's capacity to recruit from affected populations.

While there has been no systematic research conducted on CAFGU recruitment in the Philippines, anecdotal evidence can be illustrative: In 2011, I aided a relief team in Lanao Del Norte province, outside of Illigan City, following tropical storm Sendong. A local non-governmental organization, ECOweb, was responsible for relief provision, but the AFP, including some CAFGU soldiers, offered military escorts to protect from possible MILF attacks. During the project, I had the opportunity to speak informally with several of these individuals, as well as CAFGU members stationed in each recipient village, about their motivation for joining. A frequently cited rationale concerned economic hardships, including crops and livelihoods lost to flooding, and the attractiveness of regularized income. While it is unclear whether these motives emerge systematically across the country, or what influences Sendong's flooding had on these discussions, research from other conflicts provides supportive evidence. Arjona and Kalyvas (2009) assess the determinants of counterinsurgent recruitment with survey data of former Columbian paramilitaries. They find that civilians join for reasons that largely mirror those that motivate insurgent membership. The only distinction might be that material incentives (as opposed to ideological concerns) play an even larger role in decisions to support the government than in those to support insurgents.

In addition, the process of providing humanitarian assistance in the wake of a disaster can also improve civilian perceptions of the military in contested territories, which can assist military forces in insurgent suppression. In effect, humanitarian relief operations—including resource provision, development assistance, and population security—resemble those accompanying a "hearts and minds" style counterinsurgency strategy, a point leading one practitioner to state: "… disaster relief is counterinsurgency, only no one is shooting at you (yet)" (Webster, 2010, p. 1). Bennett (2010) work corroborates these claims, finding that performing "good works" in the community, including the dispensation of humanitarian aid, can increase military forces' success at mobilizing civilian support, a process he calls "counter-recruitment". A key effect of increasing civilian support is enhanced intelligence gathering, which can facilitate attacks against insurgent groups and escalate the level of violence in conflict (Condra & Shapiro, 2012).

If precipitation shocks can enable military forces to recruit new members and supporters, build local support, and enhance intelligence gathering, then the level of conflict violence in these areas should reflect this outcome. Hypothesis two states (H2):

H2. Precipitation shocks increase government violence against insurgent groups.

Hypotheses 1 and 2 enable us to empirically assess the link between precipitation shocks and conflict escalation. They are predicated on the expectation that declining resource access and lost livelihoods can increase individuals' motives and incentives for conflict, provide opportunities for combatant groups to mobilize new members and supporters, and create tactical advantages that facilitate conflict violence. The outcome should heighten conflict in vulnerable locations. In contrast, the alternative threat reduction model suggests that the same resource and subsistence crises that reduce opportunity costs for individual conflict participation might also undermine the capabilities of combatant groups to engage in warfare by limiting their ability to feed and pay fighters. If these

[1] In 2010, Republic Act 10121 modified the management structure of the National Disaster Coordinating Council and renamed it the National Disaster Risk Reduction and Management Council; however, the basic functions at the local level remain the same, including opportunities for political malfeasance.

assumptions are correct, then precipitation shocks might actually reduce conflict severity, as groups adjust strategic considerations to accommodate these concerns. These insights inform Hypothesis three (H3).

H3. Precipitation shocks reduce insurgent violence against governmental forces.

Just as precipitation shocks might diminish insurgent capabilities by reducing access to resources necessary to wage combat, so too might these phenomena undermine the state's ability to suppress insurgent groups. A common assumption in the environmental security literature is that environmental crises can decrease state capacity for conflict suppression by simultaneously reducing taxation revenue and increasing domestic spending needs for humanitarian assistance and infrastructure repair (Kahl, 2006). As a result, conflict severity should decline, as governments might be less likely to expend scarce resources towards waging counterinsurgency. Hypothesis four states (H4):

H4. Precipitation shocks reduce government violence against insurgent groups.

4. The case of the Philippines

This study evaluates the impact of precipitation shocks on violence in armed intrastate conflict with data from Philippines, 2001–2007, a nation highly susceptible to climatic and hydrometeorological disasters, and mired in civil conflict for much of the post-WWII period.

The Philippines faces acute threats from precipitation variability and tropical cyclonic activity. Each year around 20 typhoons pass through the Philippine Area of Responsibility. Of those, an average of seven-eight strike land. A number of factors contribute to these phenomena: The Philippines is an archipelagic state located entirely within the tropics, and along a major typhoon belt. The northeast (October–March) and southwest (July–September) monsoon seasons deliver a substantial portion of the country's rainfall. Though the weather patterns that follow these seasons have historically been predictable, increases in the frequency of El Niño/La Niña Southern Oscillation (ENSO) episodes exacerbate proximate weather variability. El Niño, or oceanic warming, can produce drier-than-average weather patterns, which delay the onset of the rainy season and hasten its end. La Niña events increase rainfall and tropical cyclonic activity. Both of these phenomena can wreak havoc on livelihoods associated with agricultural production. While El Niño can facilitate droughts, diminish water supplies, degrade topsoil, and increase forest fire risk, La Niña can inundate crops and generate powerful storms and floods (Jose, 2009). This variability is particularly damaging for agricultural sectors because the majority of production relies on rainfall or on fragile irrigation systems. Rice crops are acutely vulnerable. Rice is the country's most abundant agricultural product, a dietary staple for 89% of the population, and the primary source of income and employment for twelve million people (FAO, 2007). More than a third of the country's approximately four million hectares of rice crops are rain-fed; and the majority of rice cultivation takes place on small farms, each averaging less than 2 ha (Estudillo & Otsuka, 2006). Thus, even relatively minor precipitation shocks can create significant livelihood challenges for individual households (Yumul, Graciano, Dimalanta, Servando, & Hilario, 2010).

The Philippines has also experienced numerous protracted insurgent conflicts since formal recognition of its independence from the United States in 1946, and still hosts a multitude of militant organizations. The present study draws data from the four largest and most violent of these groups, which together encompass range of political motivations and organizational types. First, the Communist party of the Philippines—New Peoples' Army (CPP-NPA) conflict began in 1968, with origins in the Hukbalahap revolution fought during World War II. The CPP-NPA espouses a “Marxist-Leninist-Maoist” philosophy, and employs guerilla tactics to wage a revolutionary uprising among the rural peasantry (Caouette, 2004). The group draws resources from local communities, and through revolutionary taxes imposed on mining and logging firms. At its height in 1986, the CPP-NPA possessed approximately 25,000 fighters and had an active presence in 69/80 provinces. Currently, it fields an estimated 5000–9000 insurgents, with cadres located across the archipelago. Peace talks have occurred sporadically over the years, though as of this writing, the conflict remains ongoing.

Next, the Moro National Liberation Front (MNLF) and Moro Islamic Liberation Front (MILF), an MNLF breakaway group, have been waging separatist conflicts on Mindanao, with the MNLF in operation at least the late 1960's. Both groups have fought for greater self-determination for minority Moro populations either through outright independence, or through a semi-autonomous Bangsamoro homeland that gives Moros greater control over local resources (Schiavo-Campo & Judd, 2005). The MILF splintered from the MNLF over the signing of a failed peace agreement in 1976 that shifted MNLF priorities away from independence and towards greater autonomy. The MNLF signed another peace agreement with the Philippine government in 1996, which established the Autonomous Region of Muslim Mindanao. Despite this agreement, the group has remained operative, and occasionally engages with the AFP. The MILF, with an estimated 10–15,000 fighters, the country's largest insurgent group, is also still in operation. The group signed a peace agreement with the government in 2014, agreeing to end combat and their demands for independence in exchange for greater Bangsamoro autonomy; however, the outcome of this agreement has yet to be fully determined.

Finally, the Abu Sayaaf Group (ASG), another MNLF splinter faction, is the smallest of the four, though one of the country's deadliest militant organizations. The group embraces fundamental Islamist ideology, and supports independent homeland for Filipino Muslims, as well as the creation of an Islamist super-state in SE Asia. The group operates mainly out of Jolo and the Basilan islands south of mainland Mindanao, though it has also waged in violence in Malaysia and other areas in the Philippines. In contrast to the other three groups, ASG's modi operandi include terrorist attacks on civilians, kidnappings, extortion, and beheadings. In 2016, ASG declared allegiance to the Islamic State in Iraq and Syria (ISIS), and continues to wage jihad in the country.

Figs. 1 and 2 display the spatial and temporal distributions of conflict violence in the Philippines from 2001 to 2007. As these figures indicate, while there is some clustering, violence in the country during this time period is relatively persistent across time and space.

5. Data

The unit of analysis in this study is the Philippine province/year; and the dataset includes information for 78/81 provinces from 2001 to 2007. Sub-state data is advantageous because it can facilitate more parsimonious statistical modeling, and because data reliability should be higher, owing to more homogenous data collection methods. However, the greatest advantage of these data emerges from increased spatial precision. Studies that rely on highly aggregated environmental variables can be at a greater risk for both Type 1 and Type 2 error because the variables in question might not capture potentially extensive sub-state variation. For

example, a country-level precipitation estimate could depict an "average" year, despite the possibility that one region might be abnormally dry and another abnormally wet. This issue can be problematic if one seeks to assess these variables' effects on armed group behavior, because insurgencies are often regional in scope. Though over-aggregation can also be an issue for sub-state data, the Philippine province is relatively small, averaging only 3945 km^2, or slightly larger than the US state of Rhode Island. Thus, there is a greater likelihood that the climatic variables capture precipitation shocks in proximity to where intra-state conflict occurs. There is also good reason to believe that environmental phenomena occurring within individual Philippine provinces can influence provincial-level violence. The MILF, MNLF, and ASG are all localized, operating entirely or primarily in nine-ten provinces in Mindanao. Thus, there is a greater likelihood that conflict violence results largely from local processes. The CPP-NPA insurgency is the only truly nation-wide conflict, though only full-time cadres are expected to be available for relocation. Travel is not required for group membership, and many of the group's part-time fighters, and virtually all of their material supporters and civilian collaborators operate in proximity to their homes. The same is true for CAFGU units, who are usually stationed and operate within or near their home villages. Indeed, knowledge of local terrain and access to local social networks are among the key benefits CAFGU units provide to the AFP (Reyeg & Marsh, 2011).

5.1. Dependent variable

The dependent variables (DV) estimate violence in armed intra-state conflict in the Philippines.[2] The primary measures, *Insurgent Attacks* and *Government Attacks*, are count variables that gauge the number of attacks insurgent groups and governmental forces, respectively, instigate against the opposition in a given province/year. *Insurgent Attacks* includes attacks perpetrated by the CPP-NPA, MILF, MNLF, and ASG. *Government Attacks* include attacks that the Armed Forces of the Philippines (AFP) initiated against each of these groups. As secondary measures, I also incorporate variables that estimate conflict severity, including: insurgent and government combat deaths (*Insurgent KIA* and *Government KIA*), and insurgent and government casualties (*Insurgent Casualties* and *Government Casualties*). *Casualties* combine deaths and injuries into a single category. I employ *Attacks* as the primary measure because what occurs during a battle can be more stochastic than variations in the initiation of attack. Nevertheless, because the severity measures are logical outcomes of the intensity measures—more attacks should imply more deaths and injuries—employing both can increase the robustness of the analysis.

Data for these variables are drawn from Berman, Callen, Felter, and Shapiro (2011) who with the help of researchers working through the Empirical Studies of Conflict Project, compiled the data from: "… unclassified details of over 22,245 individual internal security incidents reported by the Armed Forces of the Philippines." The AFP sourced the incident data "… from the original field reports of every operational incident reported during this period to the Armed Forces of the Philippines' Joint Operations Center by units conducting counterinsurgency and other internal security operations" (504). Following the compilation of the incident-level files, the authors aggregated the data to the province-year.

Two potential drawbacks of this dataset are worth discussing:

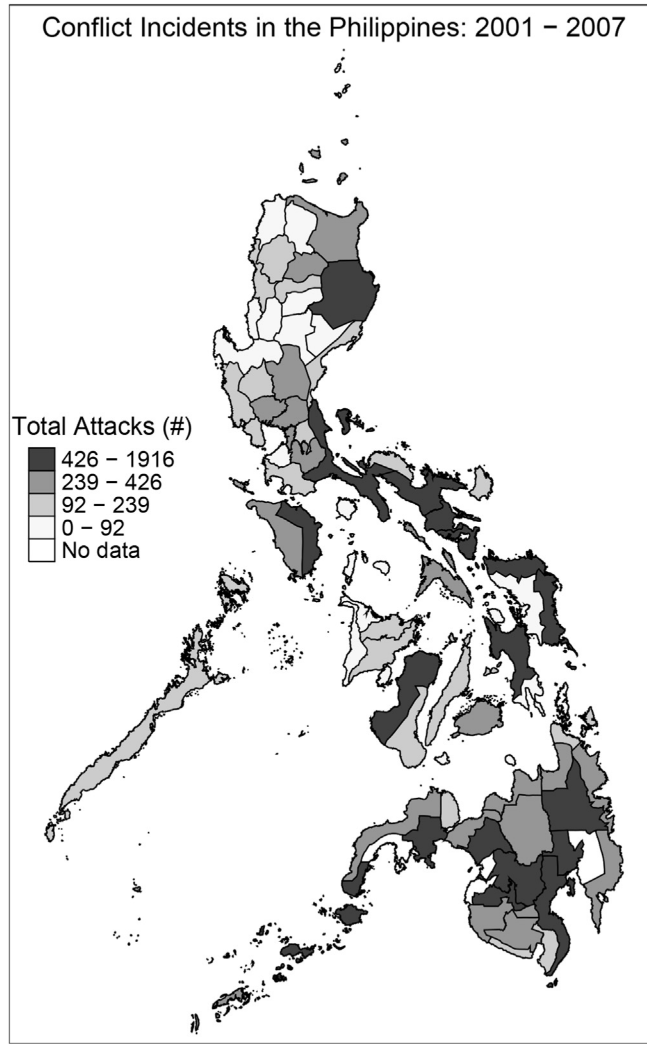

Fig. 1. Spatial distribution of conflict incidents in the Philippines: 2001–2007.

First, the data are sourced from the AFP, an institution that is also a party in each of these conflicts. Thus, there is a possibility the data might be skewed in some way so as to cast a favorable light on AFP efforts. However, the nature of the data collection in this project suggests that if a bias does exist, there is little reason to suspect it to be non-random. Because the data were compiled from individual incident level reports transmitted through official military communications channels, it is likely that operations staff did not initially intend them to be released publically. Moreover, such an endeavor would require a large number of field commanders across multiple AFP units coordinating a campaign of misinformation over a number of years for motives that, at least on the surface, are unclear. Reporting higher numbers of AFP casualties or insurgent attacks might undermine mission support, but it might also compel senior leadership to shift more resources toward a particular unit. Conversely, reporting higher numbers of insurgent casualties or government attacks might boost perceptions of mission success, but it might also undermine resource access, and result in greater incidences of mission failure.

Second, the dataset includes information only on the four largest and most significant armed groups in the Philippines. The result is that minor groups and sub-groups, and instances of small-scale political violence, including riots/protests, communal conflict, and criminal violence, are omitted. While more comprehensive

[2] A correlation matrix for all variables used in this study is available in Appendix A.

data might be desirable, their omission should not undermine this study's conclusions. First, the hypotheses concern a particular type of violence—that associated with ongoing insurgencies. Lesser types of collective violence do not necessarily fall within the explanatory scope of this piece. Second, given that these are the four largest and most well established groups in the country, there should be increased confidence in the relative continuity of group-level mobilization tactics, and in the likelihood that each were the target of sustained counterinsurgency campaigns. Finally, although the motivations for each conflict are distinct, each group has historically drawn recruits from ethnically and economically marginalized populations who are heavily reliant on agricultural production as a means of income generation, thus making their livelihoods similarly vulnerable to adverse environmental shocks. This homogeneity is beneficial because it allows for greater comparability across cases.

5.2. Independent variables

The primary independent variable in this study, *Rainfall,* measures standardized deviations in inter-annual precipitation totals from the panel mean for each Philippine province. The formula for calculating this measure is $(\mathscr{X}_{it} - \overline{\mathscr{X}_i})/\sigma_i$, where $\overline{\mathscr{X}_i}$ is the panel mean for province *i*, $\mathscr{X}_{it}$ is the precipitation estimate for province *i* at time *t*, and σ_i is province *i*'s standard deviation. This process results in a standardized precipitation estimate with a mean of approximately zero (7.64e-08), a range from −2.01 to +2.4, and a standard deviation of 0.94.

Data for these variables are drawn from the Tropical Rainfall Measurement Missions (TRMM), a project initiated in 1997 as a joint effort between NASA and the Japan Aerospace Exploration Agency to monitor rainfall over tropic and sub-tropic latitudes. The dataset, the TRMM Multi-Satellite Precipitation Analysis-Real Time Version 7 (3B42-RT), is developed using satellites that provide combined microwave-infrared precipitation estimates from −50° to +50 latitude at a spatial resolution of 0.25 × 0.25°, and is considered among the best satellite-based precipitation datasets available (Tan, Ibrahim, Duan, Cracknell, & Chaplot, 2015). Satellite-based data (as opposed to rain gauge data) are especially advantageous for archipelagic landmasses such as the Philippines, because they generate precipitation estimates over land and sea. This feature can reduce the distortionary effects that arise from interpolating precipitation data from gauges on non-contiguous landmasses (Qian, 2008). Data for Version 7 are available beginning in March 2000.

I include *Temperature* because climate change and ENSO cycles also correlate with variations in temperature, and because temperature increases can decrease agricultural yields. The temperature variable is calculated as a mean deviation using the same formula discussed previously. Temperature data are drawn from the Terrestrial Air Temperature: Gridded Monthly Time Series dataset (Version 3.01) compiled by Willmott and Matsuura (2012). Estimates of temperature means are recorded at the station-level and interpolated to a 0.5 × 0.5° lat/long grid. Data for both *Temperature* and *Rainfall* were aggregated to the provincial level using an area-weighted average of gridded-cell values.

Employing climatic data is advantageous because rainfall and temperature are entirely exogenous to conflict processes. However, a drawback of these measures is that they are unable to directly assess whether mean deviations derive from slightly wetter/drier than average weather over the course of an entire year, or whether they are driven by a few isolated extreme events. To account for this weakness, I incorporate two additional variables to approximate precipitation shock: First, *Typhoons,* gauges the percentage of the population that typhoons affect in a given province/year. While *Typhoons* cannot capture instances of negative shocks (drought), the population impacts resulting from the flooding, surges, and high winds that occur during these storms enables direct estimation of the impact of extreme precipitation events. The typhoon data for this variable were hand-coded from the archives of the Natural Disaster Risk Reduction and Management Council Operations Center (NDRRMC-OpCen) in Manila, Philippines. NDRRMC-OpCen maintains records on the majority of typhoons, and all large typhoons, that have inundated the Philippines since the late 1990's.

Second, I include *Rainfed Rice*, a variable that measures the percentage of provincial land area under cultivation with rain-fed rice crops. In the Philippines, rain-fed rice is non-irrigated, grown largely by smallholders, and contributes significantly to local consumption. The utility of this measure derives from its ability to capture the impact of precipitation shocks on agricultural output vital for rural livelihoods and subsistence. Because a key portion of

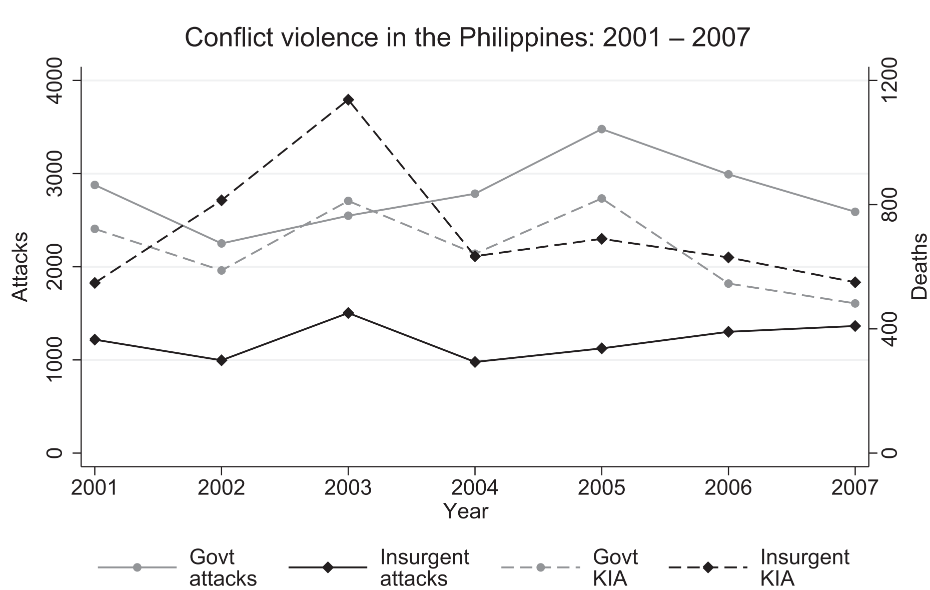

Fig. 2. Temporal distribution of conflict incidents and deaths in the Philippines, 2001–2007.

Table 1
Precipitation deviations and the incidence of conflict violence.

	All		Insurgent attacks		Government attacks	
	1A	2A	3A	4A	5A	6A
Rainfall	0.295***	0.161**	0.262***	0.131*	0.298***	0.171**
	(0.062)	(0.065)	(0.075)	(0.071)	(0.076)	(0.08)
Rainfall sq.	0.349***	0.225***	0.308***	0.225***	0.370***	0.219***
	(0.071)	(0.055)	(0.076)	(0.07)	(0.072)	(0.054)
Temperature	0.021	0.011	0.006	−0.035	0.029	0.03
	(0.057)	(0.047)	(0.074)	(0.062)	(0.057)	(0.048)
HDI		−0.058***		−0.070***		−0.053***
		(0.01)		(0.013)		(0.01)
Muslim pop.		0.008		0.002		0.011**
		(0.005)		(0.004)		(0.005)
Unemployment		−0.017		−0.002		−0.025
		(0.033)		(0.038)		(0.032)
Neighbor Conf.		0.635*		0.588		0.653**
		(0.342)		(0.422)		(0.31)
Constant	−9.86***	−7.57***	−10.96***	−8.09***	−10.26***	−8.20***
	−0.191	(0.55)	−0.181	(0.60)	−0.205	(0.56)
Observations	525	525	525	525	525	525
Provinces	75	75	75	75	75	75

Notes: Dependent variable: attacks. Province clustered standard errors in parentheses. Coefficients and standard errors for year binary variables are omitted for presentation. To control for population scale, the coefficient for provincial population is fixed to unity using the "exposure" option in STATA.
*p > 0.10 **p > 0.05, ***p > 0.01.

my argument concerns the impact these shocks have on the opportunity costs of conflict participation, and because agricultural losses can strongly influence these costs, assessing the relationship between crop production and conflict violence should provide a robust test. Moreover, the fact that the crops are not irrigated means that they are acutely sensitive climatic disruptions. In model sensitivity testing, I experimented with an alternative approximation of *Rainfed Rice* that measures production output in tons produced/Km^2. Results from models including these measures are consistent across estimations, which is not surprising because the variables are highly correlated ($\rho = 0.96$). Data for *Rainfed Rice* are drawn from the Philippine Statistical Authority. To partially mitigate endogeneity concerns, I apply a 1-year lag to both *Typhoons* and *Rainfed Rice.*

5.3. Control variables

The use of sub-state data obviates the need to include many control variables commonly employed in cross-national studies. However, there still exists sub-national variation in economic performance, development, demography, and conflict violence, which might explain the outcome independent of the primary variables of interest.

Unemployment estimates provincial unemployment rates

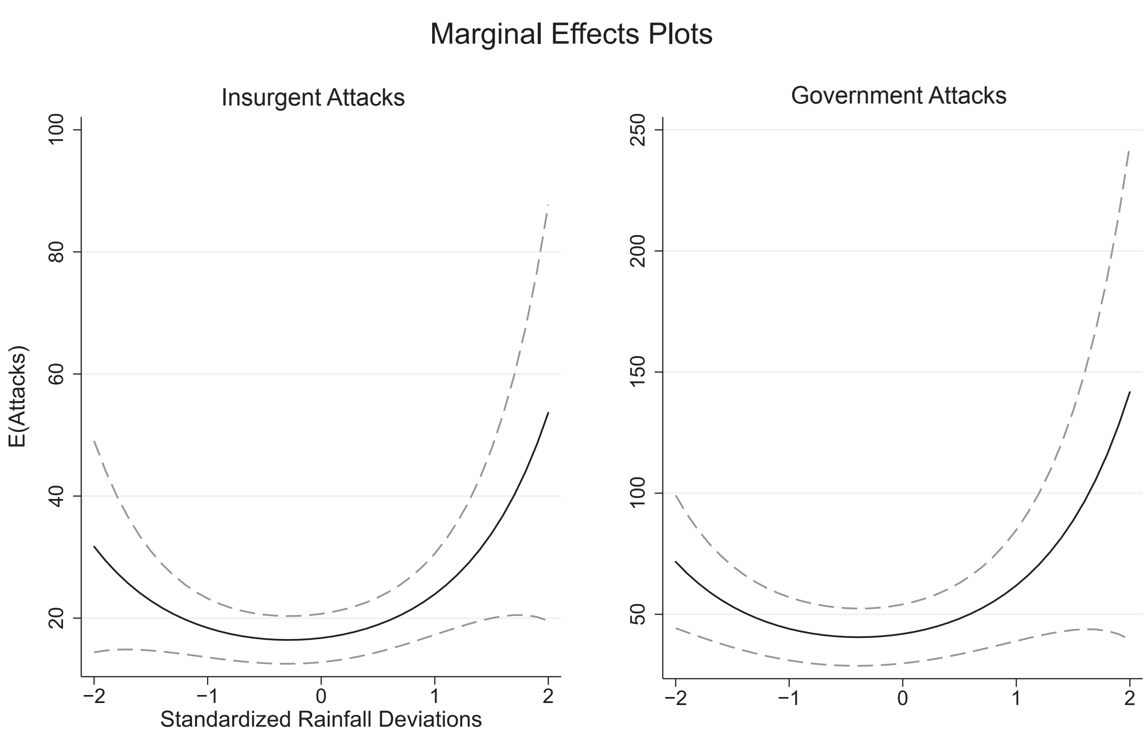

Fig. 3. Marginal effects plots.

Table 2
Typhoons, rice, and the incidence of conflict violence.

	All attacks		Insurgent attacks		Government attacks	
	1A	2A	3A	4A	5A	6A
Typhoons	1.070***		1.129***		1.007***	
	(0.326)		(0.375)		(0.342)	
Rainfed rice		−0.062***		−0.058***		−0.064***
		(0.016)		(0.017)		(0.016)
HDI	−0.061***	−0.065***	−0.073***	−0.074***	−0.057***	−0.061***
	(0.01)	(0.011)	(0.014)	(0.013)	(0.01)	(0.011)
Muslim pop.	0.011**	0.008*	0.005	0.003	0.013**	0.010**
	(0.006)	(0.004)	(0.005)	(0.004)	(0.006)	(0.005)
Unemployment	−0.02	−0.019	−0.002	0.002	−0.028	−0.028
	(0.03)	(0.031)	(0.039)	(0.036)	(0.028)	(0.029)
Neighbor conf.	0.809***	0.675**	0.772**	0.617	0.804***	0.690**
	(0.309)	(0.327)	(0.379)	(0.415)	(0.281)	(0.286)
Constant	−7.41***	−6.86***	−8.03***	−7.60***	−7.98***	−7.40***
	(0.49)	(0.531)	(0.58)	(0.557)	(0.49)	(0.549)
Observations	546	532	546	532	546	532
Provinces	78	76	78	76	78	76

Notes: Dependent variable: attacks. Province-clustered standard errors in parentheses. Coefficients and standard errors for year binary variables are omitted for presentation. To control for population scale, the coefficient for provincial population is fixed to unity using the "exposure" option in STATA.
*p > 0.10 **p > 0.05, ***p > 0.01.

using data from the Republic of the Philippines Census Organization's quarterly Labor Force Survey. In including this variable, I follow Berman, Callen, et al. (2011) who find unemployment to exhibit a negative correlation with violence in insurgencies in Afghanistan, Iraq, and the Philippines. Contrary to the conventional expectation that unemployment should increase conflict violence by reducing the opportunity costs of insurgency, these authors argue that 1) the effects of unemployment can reduce the price of intelligence information that government forces purchase from locals on insurgents; and 2) that attempts to restrict insurgent activity through enhanced security measures reduces economic activity and exacerbates unemployment. Given the plausibility of all explanations, I remain agnostic regarding the likely outcome of the unemployment variable in this analysis. Data availability covers the years 2000–2003, and 2006. To extend the dataset, I interpolate these data for the years 2004 and 2005, and extrapolate to 2007.

Muslim pop. is a time-invariant measure of the percentage of a provincial population that is Muslim, and is included to capture ethnic grievances associated with the Muslim-separatist conflicts on the southern island of Mindanao where Islam is the primary religion. Data for both *Muslim pop.* and *Unemployment* were drawn from Berman, Callen, et al. (2011).

HDI references the Human Development Index in Philippine provinces. The HDI is a composite index that captures development in terms of residents' life expectancy, educational attainment, and income levels. I include this measure to account for the possibility that provinces with higher levels of economic development are less likely to experience violence, a common finding in conflict studies. HDI scores for each province were calculated in 2000, 2003, and 2006. Missing values were interpolated and extrapolated. Provincial data for HDI was drawn from the Philippine Human Development Network (HDI, 2016).

Finally, civil war literature has repeatedly identified a spatial dependence whereby the presence of civil conflict in a given jurisdiction increases the risk of violence in proximate regions via an escalation or contagion effect (Schutte & Weidmann, 2011). I therefore include *Neighbor Conflict* to estimate the impact of conflict violence in neighboring provinces. The variable is binary, taking a value of 1 if there is conflict violence in a neighboring province/year, and zero otherwise.

6. Methodology, results, and discussion

I use negative binomial regression to model the effects of precipitation extremes on violence in civil conflict. Negative binomial models are used to analyze count data that is over-dispersed—-when the conditional variance exceeds the conditional mean. Negative binomial regression is similar to the Poisson regression, but possesses an extra parameter that corrects for over-dispersed data. Like Poisson models, a linear combination of independent variables is used to predict the log of the outcome. Unless otherwise noted, all models are run with province-clustered robust standard errors. I also include year fixed-effects to account for unobserved factors occurring in a particular year that might affect the outcome of interest. To control for population, I employ the "exposure" option in STATA to fix the coefficient for provincial population to unity, though including this variable as a predictor does not substantively alter the findings.

As a robustness check, I estimate all negative binomial models with conditional province-level fixed effects. In theory, including fixed effects is useful because it enables one to control for potential unobserved unit-specific heterogeneity. However, in negative binomial models, the legitimacy of this assumption has been questioned because the conditional fixed effects method permits unit-specific variation in the dispersion parameter instead of the conditional mean (Allison & Waterman, 2002). The result is that static predictor variables, which would ordinarily be excluded from fixed effects models, return non-zero and often statistically significant coefficients. Accordingly, I also estimate fixed effects Poisson models to assess model sensitivity. The results across all model sets are highly consistent, which lend further confidence in the findings.[3]

Table 1 reports the coefficients and standard errors of the effects of precipitation shocks on the incidence of attacks initiated by both insurgent and government forces, and the combination of the two. The models include the *Rainfall* variable and its squared term, the *Temperature* variable, along with year fixed effects and province-clustered robust standard errors. Models 1, 3, and 5 report reduced form estimates, while Models 2, 4, and 6 include the full suite of control variables. Table 1 reveals evidence of a

[3] Results for all fixed effects models are included in Appendix A.

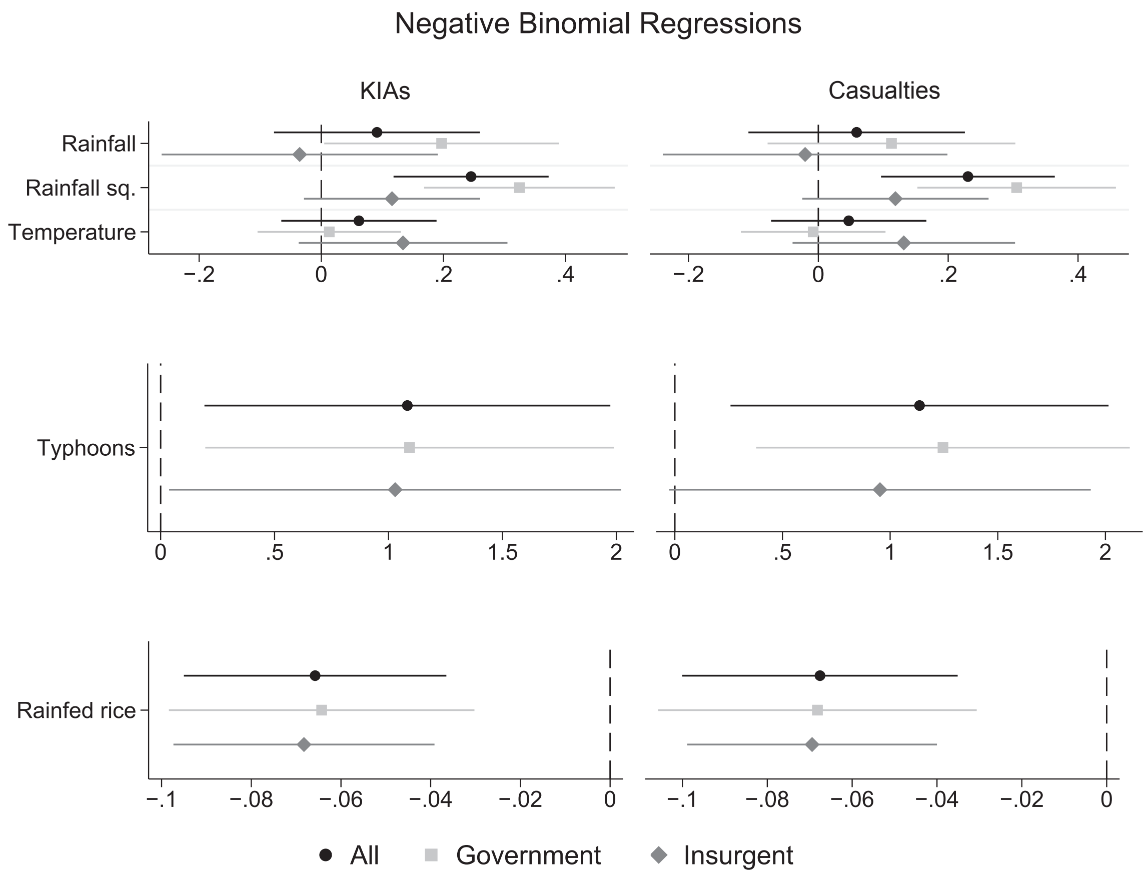

Fig. 4. Negative binomial regressions. Models are run with country-clustered errors, year fixed effects, and the full suite of control variables.

curvilinear effect—that conflict incidents are more common in times of both scarce and excess precipitation, as the squared predictor term is positive and significant across models. Wald tests indicate that the inclusion of the both the linear and quadratic precipitation variables improves model fit to a statistically significant degree. The findings provide robust support for H1 and H2, which postulate that deviations from mean precipitation levels should have a positive effect on violence in civil conflict. These findings also support prior literature that finds a curvilinear effect between rainfall and communal violence (Raleigh & Kniveton, 2012) and rainfall and low-level political violence (Hendrix & Salehyan, 2012). Conversely, little evidence was marshaled for H3 and H4, which suggest that precipitation shocks should decrease these effects.

In contrast to precipitation, this analysis reveals minimal correlation between deviations from mean temperatures and the incidence and severity of civil conflict in the Philippines, as the *Temperature* variable fails to achieve statistical significance in any of the estimated models.

The magnitude of the effect of excess precipitation on conflict violence can be considerable. A one standard deviation increase in precipitation increases the expected count of insurgent-initiated attacks from seventeen to twenty-three, an increase of 35%. The effect is even larger for government-initiated events: A one standard deviation increase raises the expected count of these by 43%, from forty-two to sixty. The expected count of all incidents rises 43%, from fifty-eight to eighty-three. The impact of negative deviations is less acute: A one standard deviation decrease in precipitation increases the expected number of insurgent attacks 6%, from seventeen to eighteen, and government-initiated attacks 2%, from forty-two to forty-three. One possible explanation for this disparity concerns the impact of livelihood adaptation capacity. While droughts can take weeks or months to render their most damaging effects, flooding and inundation occurs rapidly, often with little warning. Thus, it might be that the speed of onset and livelihood losses that follow can partially (though not completely) mediate the impact of precipitation shocks on conflict severity. Another possibility is that while irrigation can alleviate the impact of below-average rainfall, farmers can do little to compensate for the damage caused by too much (Alam et al., 2011).

Fig. 3 provides a graphical display of the relationship between standardized precipitation deviations and expected counts of *Insurgent* and *Government Attacks*.[4] As this graph indicates, there exists a strong concave relationship between precipitation and conflict violence, with less violence associated with lower mean deviation.

Table 2 reports negative binomial coefficient and standard errors from models that estimate the impact of *Typhoons* and *Rainfed Rice* on conflict violence. In Table 2, models 7, 9, and 11 estimate *Typhoons'* effects on all conflict incidents, and insurgent and government-initiated attacks, respectively, while Models 8, 10, and 12 follow suit with *Rainfed Rice*. These results are consistent with those presented in Table 1, and provide strong additional evidence in support H1 and H2. The coefficients for the *Typhoons* variables are all positively signed and statistically significant, while those for *Rainfed Rice* are negative and significant. Moreover, these effects

[4] A table reporting the marginal effects and confidence intervals for the full range of independent variables is included in Appendix A.

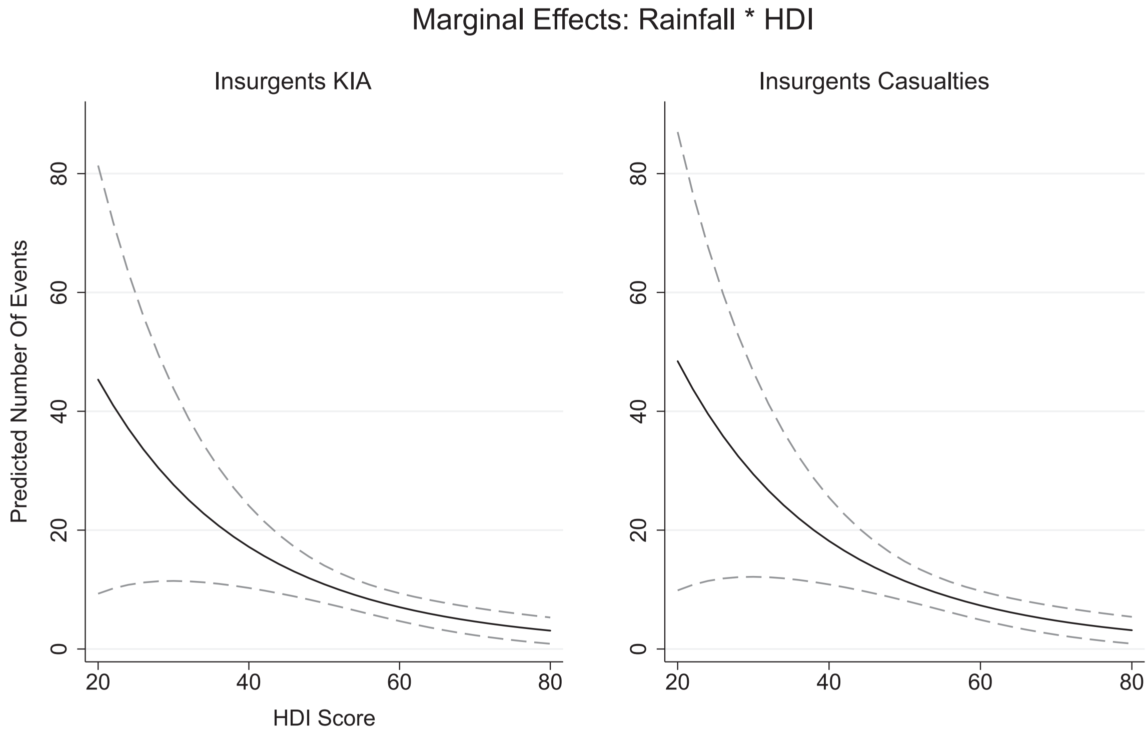

Fig. 5. Marginal effects interaction plot.

appear to be linear, as the inclusion of quadratic terms in robustness testing yielded insignificant results. The substantive effect of these variables on the outcome is also strong. A one standard deviation increase in typhoon magnitude elevates the expected count of insurgent and government attacks by 20% and 19%, respectively, while a one standard deviation decrease in the area of rain-fed rice under cultivation (in Km^2) increases the count of these attacks by 33% for insurgents and 37% for the government. These findings corroborate prior work that has found natural disasters to exert a positive impact on conflict violence and terrorism (Berrebi & Ostwald, 2011; Raleigh & Kniveton, 2012), as well as those that reveal similar relationships with food production (Wischnath & Buhaug, 2014).

In addition to finding support for H1 and H2, a notable feature across all *Attack* models is the consistency of effect that precipitation shocks and agricultural losses can generate on both government and insurgent-initiated violence. While one might expect insurgents to either suffer disproportionate costs from declines in resource availability (Salehyan & Hendrix, 2014), or reap disproportionate benefits from heightened recruitment (Wischnath & Buhaug, 2014), these findings indicate that precipitation shocks can enable both insurgent and counterinsurgent forces to amplify their capabilities to attack in relatively equal proportions. These findings also suggest that future studies should attempt to account for not only the effects of resource scarcity on insurgent capabilities, but on governments' as well.

In line with results from models of conflict incidence, I also find some evidence that precipitation shocks can heighten measures of conflict severity: *Insurgent KIA, Government KIA, Insurgent Casualties,* and *Government Casualties.* Fig. 4 displays the coefficient estimates and 95% confidence intervals for *Rainfall* (linear and squared term), *Typhoons,* and *Rainfed Rice* on these variables.[5] Two features of the conflict severity models are particularly noteworthy: First, while models estimating the impact of *Typhoons* and *Rainfed Rice* are consistent with those estimating conflict incidence, severity models that include linear and quadratic precipitation variables as the primary predictors are less stable. As mentioned previously, one potential explanation for this variation is that what happens in a battle—deaths and casualties—can be more random than the initiation of attacks. In other words, while in general the number of fighters can strongly influence the number of injuries and deaths in battle, such is not always the case. Second, models estimating the severity of insurgent attacks on government forces (*Government KIA and Government Casualties*) are more robust than those estimating the effects of government attacks on insurgents (*Insurgent KIA* and *Insurgent Casualties*). One possibility for this outcome might be that the military's provision of humanitarian aid disproportionately exposes soldiers to attack.

In model sensitivity testing, I experimented with a range of possible interaction effects between *Rainfall, Typhoons, and Rainfed Rice,* and each of the control variables. The results of these interactions were largely inconsistent and insignificant, with one notable exception: interactions between *Rainfall* and *HDI* yielded negative and statistically significant effects on models estimating *Insurgent KIA* and *Insurgent Casualties*. This finding reveals that precipitation shocks generate greater impact on conflict severity at lower levels of HDI and taper at higher levels, and is consistent with causal logic informing H1 and H2. Notably, this interaction only appears to be significant for governmental attacks on insurgents, and does not yield a statistically significant impact for insurgent groups. Fig. 5 provides a graphical depiction.[6] This outcome might indicate that the

[5] A table reporting the estimated coefficients and standard errors from these regressions is available in Appendix A.

[6] A table reporting the estimated coefficients and standard errors from these regressions is available in Appendix A.

impact of shocks on livelihoods in acutely deprived areas can increase conflict participation, especially for those for whom paramilitary service provides a viable alternative, an impact which would tangentially support work by Arjona and Kalyvas (2009). These findings might also indicate that the tactical advantages afforded to governmental forces who provide humanitarian assistance in economically deprived areas outweigh similar efforts by insurgent groups.

Turning to the effects of the control variables on the outcome, I find robust support for a negative relationship between HDI and conflict severity, and tentative support for the same relationship with unemployment. The latter result overlaps with that of Berman, Callen, et al. (2011) who argue that unemployment increases the ability of combatant groups to purchase logistical information from civilians that can increase groups' vulnerability to attack. I also find partial evidence for a positive relationship between the proportion of the provincial population that is Muslim and conflict violence. This finding is as expected because the Moro provinces on Mindanao have historically been associated with three of the conflicts included in this analysis: the MILF, MNLF, and ASG. Finally, I find modest support for a conflict-contagion effect, as *Neighbor conflict* is positive and statistically significant across several of the models.

7. Conclusion

This analysis employs micro-level data from the Philippines to test key environmental security arguments on the relationship between climate change and conflict. I find that precipitation shocks increase violence in armed intrastate conflict in the Philippines, as conflict incidents, battle deaths, and casualties rise in accordance with excess rainfall, typhoons, and declines in agricultural productivity. These findings support prior studies, which have found positive correlations between natural disasters and conflict, and curvilinear relationships between precipitation variability and conflict (Berrebi & Ostwald, 2011; Hendrix & Salehyan, 2012; Raleigh & Kniveton, 2012).

Additionally, this study identifies that precipitation shocks induce a relatively homogenous effect on conflict outcomes regardless of the identity of the agents of violence. This finding is important because a commonly held assumption is that climate change should decrease state capabilities to counter insurgent threats. While this assumption might hold under certain circumstances, this study finds that climatic phenomena can also provide opportunities for governments to exploit population vulnerabilities to motivate additional support and cooperation, which can increase governmental capabilities to find and attack insurgents. Future research should consider the scope conditions that determine this effect to better understand how climate change will influence the trajectory of armed intra-state wars.

The results of this study hold policy implications for the future. Scientists anticipate changes in the earth's climate to increase the incidence of El Niño/La Niña Southern Oscillation (ENSO) events, and to intensify the pace of the water cycle—the processes of evaporation, condensation, and precipitation that propel water through the hydrosphere. Both of these mechanisms are expected exacerbate precipitation variability in tropic and sub-tropic latitudes (Durack, Wijffels, & Matear, 2012Latif & Keenlyside, 2008; Durack, Wijffels, and Matear, 2012). In nations like the Philippines, while aggregate precipitation might remain static or decline slightly, the rain that does fall will do so in shorter and more intense intervals. Dry places become dryer and wet places wetter. Droughts become longer, and storms more violent. Given that these dynamics do not bode well for conflict violence, policymakers might consider policies that help individuals to mitigate the livelihood damages climatic changes provoke as a means to reduce conflict violence.

Appendix A

Marginal effects and correlation matrix

Table 1A
Marginal effects by key independent variable.

Indep. variable	Agent	Dep. variable	Mean, CIs	+1sd, CIs	Change	−1sd, CIs	Change
Rainfall	Insurgents	Inc	17, 13–21	23, 17–29	35%	18, 13–23	6%
Rainfall	Insurgents	KIA	11, 6–16	12, 6–17	9%	13, 6–19	18%
Rainfall	Insurgents	Cas	11, 6–17	13, 7–18	18%	13, 7–19	18%
Rainfall	State	Inc	42, 30–54	60, 38–81	43%	43, 31–56	2%
Rainfall	State	KIA	9, 6–12	15, 9–21	67%	10, 7–14	11%
Rainfall	State	Cas	17, 11–23	25, 15–35	47%	20, 12–29	18%
Typhoons	Insurgents	Inc	18, 14–23	22, 16–27	22%	15, 11–20	−17%
Typhoons	Insurgents	KIA	12, 6–19	15, 6–23	25%	10, 4–16	−17%
Typhoons	Insurgents	Cas	13, 6–20	15, 7–23	15%	11, 5–17	−15%
Typhoons	State	Inc	46, 30–61	54, 25–53	17%	39, 25–53	−15%
Typhoons	State	KIA	11, 7–15	13, 8–19	18%	9, 5–13	−18%
Typhoons	State	Cas	20, 11–30	25, 13–36	25%	16, 8–25	−20%
Rainfed rice	Insurgents	Inc	18, 14–22	13, 10–17	−28%	24, 17–31	33%
Rainfed rice	Insurgents	KIA	11, 7–14	7, 5–10	−36%	15, 9–20	36%
Rainfed rice	Insurgents	Cas	11, 7–15	8, 5–10	−27%	16, 10–21	45%
Rainfed rice	State	Inc	43, 32–54	31, 22–40	−28%	59, 41–78	37%
Rainfed rice	State	KIA	10, 7–13	7, 5–10	−30%	14, 9–19	40%
Rainfed rice	State	Cas	18, 13–24	13, 9–18	−28%	26, 16–36	44%

Notes: Results from negative binomial regressions with year fixed effects, province-clustered standard errors, and full suite of control variables. “Ins” = insurgents; ”Inc” = Attacks; “KIA” = killed in action; “Cas” = casualties; “CIs” = confidence intervals.

Table 2A
Correlation matrix of key variables.

	Ins. inc.	Gov. inc.	Ins. KIA	Gov. KIA	Ins. cas.	Gov. cas.	Rainfall
Ins. inc.	1						
Gov. inc.	0.68	1					
Ins. KIA	0.61	0.67	1				
Gov. KIA	0.69	0.73	0.69	1			
Ins. cas.	0.60	0.67	0.99	0.69	1		
Gov. cas.	0.51	0.53	0.55	0.79	0.56	1	
Rainfall	0.14	0.08	0	0.06	0	0.09	1
Temp.	−0.03	0.05	−0.01	−0.01	0	0.01	0.08
Typhoon	0.03	−0.02	−0.05	−0.03	−0.05	−0.02	0.01
Rice (area)	−0.06	−0.09	−0.07	−0.10	−0.06	−0.08	−0.03
Rice (tons)	−0.07	−0.09	−0.08	−0.11	−0.07	−0.09	−0.03
HDI	−0.26	−0.25	−0.27	−0.30	−0.27	−0.26	−0.06
%Muslim	0.31	0.40	0.53	0.44	0.53	0.38	0.03
Unemp.	−0.14	−0.18	−0.15	−0.19	−0.15	−0.19	−0.09
	Temp.	**Typhoon**	**Rice area**	**Rice tons**	**HDI**	**%Muslim**	**Unemp.**
Temp.	1						
Typhoon	−0.10	1					
Rice (area)	−0.03	−0.04	1				
Rice (tons)	−0.04	−0.03	0.96	1			
HDI	−0.01	0.02	−0.14	−0.06	1		
%Muslim	0.04	−0.10	−0.06	−0.08	−0.40	1	
Unemp.	−0.02	0	0	0.05	0.49	−0.20	1

Notes: “ins” = insurgents; “gov” = government; “cas” = casualties; “unemp” = unemployment.

Negative binomial regressions

Table 3A
Precipitation deviations and the incidence of conflict violence.

	All		Insurgent attacks		Government attacks	
	1A	2A	3A	4A	5A	6A
Rainfall	0.161**	0.081*	0.131*	0.074	0.171**	0.102**
	(0.065)	(0.048)	(0.071)	(0.058)	(0.08)	(0.052)
Rainfall sq.	0.225***	0.107***	0.225***	0.125***	0.219***	0.106**
	(0.055)	(0.041)	(0.07)	(0.048)	(0.054)	(0.045)
Temperature	0.011	0.017	−0.035	−0.066	0.03	0.041
	(0.047)	(0.033)	(0.062)	(0.044)	(0.048)	(0.036)
HDI	−0.058***	−0.043***	−0.070***	−0.032***	−0.053***	−0.042***
	(0.01)	(0.007)	(0.013)	(0.009)	(0.01)	(0.007)
Muslim pop.	0.008	−0.017***	0.002	−0.014***	0.011**	−0.019***
	(0.005)	(0.003)	(0.004)	(0.004)	(0.005)	(0.003)
Unemployment	−0.017	−0.030*	−0.002	−0.035	−0.025	−0.016
	(0.033)	(0.018)	(0.038)	(0.023)	(0.032)	(0.018)
Neighbor conf.	0.635*	0.161	0.588	0.810***	0.653**	−0.113
	(0.342)	(0.238)	(0.422)	(0.271)	(0.31)	(0.249)
Constant	−7.57***	−10.29***	−8.09***	−11.59***	−8.20***	−10.36***
	(0.55)	(0.35)	(0.60)	(0.474)	(0.56)	(0.38)
Observations	525	497	525	469	525	497
Provinces	75	71	75	67	75	71
Fixed effects		X		X		X
Clustered errors	X		X		X	

Notes: Negative binomial regressions. Dependent variable: attacks. Province clustered robust standard errors in parentheses. Coefficients and standard errors for year binary variables are omitted for presentation. To control for population scale, the coefficient for provincial population is fixed to unity using the “exposure” option in STATA. *p > 0.10 **p > 0.05, ***p > 0.01.

Table 4A
Precipitation shocks and conflict severity: KIA.

DV: KIA	All		Insurgents KIA		Government KIA	
	7A	8A	9A	10A	11A	12A
Rainfall	0.091	0.085	−0.035	0.005	0.197**	0.128*
	(0.086)	(0.067)	(0.115)	(0.093)	(0.098)	(0.069)
Rainfall sq.	0.245***	0.05	0.116	−0.036	0.324***	0.170***
	(0.065)	(0.059)	(0.074)	(0.08)	(0.08)	(0.059)
Temperature	0.062	0.053	0.134	0.149**	0.013	−0.001
	(0.065)	(0.049)	(0.087)	(0.068)	(0.06)	(0.05)
HDI	−0.054***	−0.035***	−0.044***	−0.049***	−0.063***	−0.030***
	(0.011)	(0.009)	(0.012)	(0.01)	(0.012)	(0.01)
Muslim pop.	0.014**	−0.008**	0.020***	−0.003	0.008	−0.013***
	(0.007)	(0.004)	(0.007)	(0.004)	(0.007)	(0.004)
Unemployment	−0.031	−0.071***	−0.027	−0.051*	−0.047	−0.048*
	(0.032)	(0.023)	(0.033)	(0.027)	(0.036)	(0.027)
Neighbor conf.	0.501	−0.156	0.633	0.017	0.374	0.215
	(0.473)	(0.276)	(0.449)	(0.324)	(0.498)	(0.321)
Constant	−8.76***	−10.88***	−10.32***	−11.54***	−8.62***	−11.38***
	(0.619)	(0.445)	(0.647)	(0.523)	(0.643)	(0.543)
Observations	525	483	525	469	525	483
Provinces	75	69	75	67	75	69
Fixed effects		X		X		X
Clustered errors	X		X		X	

Notes: Negative binomial regressions. Dependent variable: KIA. Province clustered robust standard errors in parentheses. Coefficients and standard errors for year binary variables are omitted for presentation. To control for population scale, the coefficient for provincial population is fixed to unity using the "exposure" option in STATA. *p > 0.10 **p > 0.05, ***p > 0.01.

Table 5A
Precipitation shocks and conflict severity: Casualties.

	All		Insurgent casualties		Government casualties	
	13A	14A	15A	16A	17A	18A
Rainfall	0.059	0.083	−0.02	−0.003	0.113	0.103
	(0.085)	(0.068)	(0.112)	(0.092)	(0.097)	(0.069)
Rainfall sq.	0.230***	0.032	0.119	−0.032	0.305***	0.135**
	(0.068)	(0.061)	(0.073)	(0.079)	(0.078)	(0.06)
Temperature	0.047	0.053	0.132	0.144**	−0.008	0.048
	(0.061)	(0.049)	(0.087)	(0.068)	(0.057)	(0.051)
HDI	−0.056***	−0.039***	−0.045***	−0.050***	−0.063***	−0.043***
	(0.011)	(0.008)	(0.012)	(0.01)	(0.012)	(0.009)
Muslim pop.	0.013**	−0.010***	0.020***	−0.003	0.009	−0.011***
	(0.007)	(0.004)	(0.007)	(0.004)	(0.007)	(0.004)
Unemployment	−0.033	−0.077***	−0.024	−0.052*	−0.048	−0.061**
	(0.035)	(0.022)	(0.033)	(0.026)	(0.039)	(0.024)
Neighbor conf.	0.5	−0.11	0.664	0.053	0.423	0.353
	(0.483)	(0.258)	(0.449)	(0.322)	(0.505)	(0.279)
Constant	−8.61***	−10.92***	−10.34***	−11.55***	−8.61***	−11.26***
	(0.61)	(0.41)	(0.64)	(0.51)	(0.64)	(0.46)
Observations	525	490	525	469	525	490
Provinces	75	70	75	67	75	70
Fixed effects		X		X		X
Clustered errors	X		X		X	

Notes: Negative binomial regressions. Dependent variable: casualties. Province clustered robust standard errors in parentheses. Coefficients and standard errors for year binary variables are omitted for presentation. To control for population scale, the coefficient for provincial population is fixed to unity using the "exposure" option in STATA. *p > 0.10 **p > 0.05, ***p > 0.01.

Table 6A
Typhoons and the incidence of conflict violence.

	All attacks		Insurgent attacks		Government attacks	
	19A	20A	21A	22A	23A	24A
Typhoons	1.070***	0.406**	1.129***	0.535**	1.007***	0.393**
	(0.326)	(0.171)	(0.375)	(0.212)	(0.342)	(0.188)
HDI	−0.061***	−0.041***	−0.073***	−0.033***	−0.057***	−0.041***
	(0.01)	(0.007)	(0.014)	(0.009)	(0.01)	(0.007)
Muslim pop.	0.011**	−0.017***	0.005	−0.015***	0.013**	−0.018***
	(0.006)	(0.003)	(0.005)	(0.004)	(0.006)	(0.003)
Unemployment	−0.02	−0.030*	−0.002	−0.039*	−0.028	−0.017
	(0.03)	(0.018)	(0.039)	(0.023)	(0.028)	(0.018)
Neighbor conf.	0.809***	0.163	0.772**	0.799***	0.804***	−0.113
	(0.309)	(0.23)	(0.379)	(0.269)	(0.281)	(0.24)
Constant	−7.41***	−10.26***	−8.03***	−11.51***	−7.98***	−10.29***
	(0.49)	(0.35)	(0.58)	(0.46)	(0.49)	(0.37)
Observations	546	511	546	476	546	511
Provinces	78	73	78	68	78	73
Fixed effects		X		X		X
Clustered errors	X		X		X	

Notes: Negative binomial regressions. Dependent variable: attacks. Province clustered robust standard errors in parentheses. Coefficients and standard errors for year binary variables are omitted for presentation. To control for population scale, the coefficient for provincial population is fixed to unity using the "exposure" option in STATA. *p > 0.10 **p > 0.05, ***p > 0.01.

Table 7A
Typhoons and conflict severity: KIA.

	All KIA		Insurgents KIA		Government KIA	
	25A	26A	27A	28A	29A	30A
Typhoons	1.083**	0.458*	1.029**	0.688**	1.092**	0.554**
	(0.454)	(0.276)	(0.506)	(0.345)	(0.457)	(0.277)
HDI	−0.055***	−0.035***	−0.046***	−0.046***	−0.065***	−0.032***
	(0.012)	(0.009)	(0.012)	(0.01)	(0.013)	(0.01)
Muslim pop.	0.018**	−0.008**	0.023***	−0.001	0.012	−0.013***
	(0.007)	(0.004)	(0.007)	(0.004)	(0.007)	(0.004)
Unemployment	−0.037	−0.074***	−0.025	−0.058**	−0.055	−0.049*
	(0.032)	(0.023)	(0.034)	(0.027)	(0.034)	(0.027)
Neighbor conf.	0.718*	−0.131	0.829**	−0.04	0.591	0.211
	(0.42)	(0.275)	(0.394)	(0.324)	(0.442)	(0.32)
Constant	−8.72***	−10.79***	−10.39***	−11.53***	−8.42***	−11.15***
	(0.57)	(0.43)	(0.59)	(0.51)	(0.61)	(0.52)
Observations	546	497	546	469	546	497
Provinces	78	71	78	67	78	71
Fixed effects		X		X		X
Clustered errors	X		X		X	

Notes: Negative binomial regressions. Dependent variable: KIA. Province clustered robust standard errors in parentheses. Coefficients and standard errors for year binary variables are omitted for presentation. To control for population scale, the coefficient for provincial population is fixed to unity using the "exposure" option in STATA. *p > 0.10 **p > 0.05, ***p > 0.01.

Table 8A
Typhoons and conflict severity: Casualties.

	All casualties		Insurgent casualties		Government casualties	
	31A	32	33	34	35	36
Typhoons	1.137**	0.454*	0.953*	0.359	1.245***	0.450*
	(0.448)	(0.261)	(0.499)	(0.273)	(0.443)	(0.256)
HDI	−0.058***	−0.038***	−0.047***	−0.046***	−0.065***	−0.044***
	(0.012)	(0.008)	(0.012)	(0.009)	(0.013)	(0.009)
Muslim pop.	0.017**	−0.010***	0.023***	0.005	0.013*	−0.011***
	(0.007)	(0.004)	(0.007)	(0.00)	(0.007)	(0.004)
Unemployment	−0.037	−0.080***	−0.022	−0.060***	−0.056	−0.062**
	(0.034)	(0.022)	(0.034)	(0.021)	(0.037)	(0.024)
Neighbor conf.	0.752*	−0.093	0.855**	−32.775	0.694	0.351
	(0.435)	(0.258)	(0.398)	(0.00)	(0.455)	(0.277)
Constant	−8.63***	−10.86***	−10.39***	21.44***	−8.52***	−11.08***
	(0.56)	(0.40)	(0.58)	(0.53)	(0.61)	(0.44)
Observations	546	504	546	469	546	504
Provinces	78	72	78	67	78	72
Fixed effects		X		X		X
Clustered errors	X		X		X	

Notes: Negative binomial regressions. Dependent variable: Casualties. Province clustered robust standard errors in parentheses. Coefficients and standard errors for year binary variables are omitted for presentation. To control for population scale, the coefficient for provincial population is fixed to unity using the "exposure" option in STATA. *p > 0.10 **p > 0.05, ***p > 0.01.

Table 9A
Rainfed rice and the incidence of conflict violence.

	All Attacks		Insurgent Attacks		Government Attacks	
	37A	38A	39A	40A	41A	42A
Rainfed rice	−0.062***	−0.045***	−0.058***	−0.049**	−0.064***	−0.039**
	(0.016)	(0.017)	(0.017)	(0.021)	(0.016)	(0.017)
HDI	−0.065***	−0.034***	−0.074***	−0.038***	−0.061***	−0.034***
	(0.011)	(0.007)	(0.013)	(0.009)	(0.011)	(0.008)
Muslim pop.	0.008*	−0.017***	0.003	−0.015***	0.010**	−0.017***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.005)	(0.003)
Unemployment	−0.019	−0.001	0.002	−0.036	−0.028	0.01
	(0.031)	(0.017)	(0.036)	(0.022)	(0.029)	(0.018)
Neighbor conf.	0.675**	0.1	0.617	0.718***	0.690**	−0.151
	(0.327)	(0.234)	(0.415)	(0.277)	(0.286)	(0.242)
Constant	−6.863***	−10.50***	−7.60***	−10.97***	−7.40***	−10.57***
	(0.531)	(0.407)	(0.557)	(0.495)	(0.549)	(0.436)
Observations	532	504	532	469	532	504
Provinces	76	72	76	67	76	72
Fixed effects		X		X		X
Clustered errors	X		X		X	

Notes: Negative binomial regressions. Dependent variable: Attacks. Province clustered robust standard errors in parentheses. Coefficients and standard errors for year binary variables are omitted for presentation. To control for population scale, the coefficient for provincial population is fixed to unity using the “exposure” option in STATA. *p > 0.10 **p > 0.05, ***p > 0.01.

Table 10A
Rainfed rice and conflict severity: KIA.

	All KIA		Insurgent KIA		Government KIA	
	43A	44A	45A	46A	47A	48A
Rainfed rice	−0.066***	−0.073***	−0.068***	−0.039*	−0.064***	−0.102***
	(0.015)	(0.018)	(0.015)	(0.021)	(0.017)	(0.021)
HDI	−0.058***	−0.037***	−0.049***	−0.042***	−0.068***	−0.039***
	(0.011)	(0.009)	(0.011)	(0.011)	(0.013)	(0.01)
Muslim pop.	0.013**	−0.009**	0.018***	−0.002	0.007	−0.011***
	(0.006)	(0.004)	(0.005)	(0.004)	(0.006)	(0.004)
Unemployment	−0.029	−0.061***	−0.015	−0.044*	−0.05	−0.044*
	(0.03)	(0.022)	(0.031)	(0.026)	(0.032)	(0.026)
Neighbor conf.	0.517	−0.223	0.626	−0.175	0.425	0.186
	(0.439)	(0.281)	(0.413)	(0.336)	(0.464)	(0.322)
Constant	−8.17***	−10.36***	−9.77***	−11.53***	−7.93***	−10.39***
	(0.568)	(0.465)	(0.569)	(0.551)	(0.644)	(0.541)
Observations	532	490	532	462	532	490
Provinces	76	70	76	66	76	70
Fixed effects		X		X		X
Clustered errors	X		X		X	

Notes: Negative binomial regressions. Dependent variable: KIA. Province clustered robust standard errors in parentheses. Coefficients and standard errors for year binary variables are omitted for presentation. To control for population scale, the coefficient for provincial population is fixed to unity using the “exposure” option in STATA. *p > 0.10 **p > 0.05, ***p > 0.01.

Table 11A
Rainfed rice and conflict severity: Casualties.

	All Casualties		Insurgent Casualties		Government Casualties	
	49A	50A	51A	52A	53A	54A
Rainfed rice	−0.068***	−0.077***	−0.069***	−0.046**	−0.068***	−0.096***
	(0.017)	(0.018)	(0.015)	(0.021)	(0.019)	(0.02)
HDI	−0.060***	−0.035***	−0.050***	−0.041***	−0.068***	−0.042***
	(0.011)	(0.009)	(0.011)	(0.011)	(0.012)	(0.009)
Muslim pop.	0.012**	−0.011***	0.018***	−0.002	0.008	−0.011***
	(0.005)	(0.004)	(0.005)	(0.004)	(0.006)	(0.004)
Unemployment	−0.031	−0.060***	−0.013	−0.042	−0.052	−0.048**
	(0.032)	(0.021)	(0.031)	(0.026)	(0.035)	(0.023)
Neighbor conf.	0.514	−0.249	0.657	−0.163	0.458	0.179
	(0.453)	(0.267)	(0.413)	(0.336)	(0.476)	(0.292)
Constant	−8.03***	−10.60***	−9.75***	−11.58***	−7.93***	−10.66***
	(0.562)	(0.45)	(0.569)	(0.548)	(0.636)	(0.488)
Observations	532	497	532	462	532	497
Provinces	76	71	76	66	76	71
Fixed effects		X		X		X
Clustered errors	X		X		X	

Notes: Negative binomial regressions. Dependent variable: Casualties. Province clustered robust standard errors in parentheses. Coefficients and standard errors for year binary variables are omitted for presentation. To control for population scale, the coefficient for provincial population is fixed to unity using the “exposure” option in STATA. *p > 0.10 **p > 0.05, ***p > 0.01.

Poisson regressions

Table 12A
Precipitation shocks and the incidence of conflict violence.

	All Attacks	Insurgent Attacks	Government Attacks
	55A	56A	57A
Rainfall	0.165***	0.180***	0.150***
	0.01	0.018	0.013
Rainfall sq.	0.136***	0.104***	0.144***
	0.009	0.015	0.011
Temperature	−0.001	−0.027*	0.01
	0.008	0.015	0.01
HDI	−0.011***	−0.012**	−0.010***
	0.003	0.005	0.003
Unemployment	0.014**	−0.007	0.024***
	0.006	0.011	0.007
Observations	497	469	497
Provinces	71	67	71

Notes: Poisson regressions with year and provincial conditional fixed effects. Dependent variable: Attacks. Coefficients and standard errors for year binary variables are omitted for presentation. *Neighbor conflict* and *Muslim pop.* dropped from model due to invariance. To control for population scale, the coefficient for provincial population is fixed to unity using the "exposure" option in STATA. *p > 0.10 **p > 0.05, ***p > 0.01.

Table 13A
Precipitation shocks and conflict severity: KIA.

	All KIA	Insurgent KIA	Government KIA
	58A	59A	60A
Rainfall	0.083***	0.056**	0.102***
	0.017	0.024	0.025
Rainfall sq.	0.061***	−0.002	0.121***
	0.015	0.021	0.021
Temperature	−0.014	0.056**	−0.078***
	0.015	0.022	0.021
HDI	0.011**	0.003	0.021***
	0.005	0.007	0.007
Unemployment	0.012	−0.029**	0.074***
	0.01	0.013	0.015
Observations	483	469	483
Provinces	69	67	69

Notes: Poisson regressions with year and provincial conditional fixed effects. Dependent variable: KIA. Coefficients and standard errors for year binary variables are omitted for presentation. *Neighbor conflict* and *Muslim pop.* dropped from model due to invariance. To control for population scale, the coefficient for provincial population is fixed to unity using the "exposure" option in STATA. *p > 0.10 **p > 0.05, ***p > 0.01.

Table 14A
Precipitation shocks and conflict severity: Casualties.

	All casualties	Insurgent casualties	Government casualties
	61A	62A	63A
Rainfall	0.106***	0.056**	0.101***
	0.016	0.024	0.021
Rainfall sq.	0.046***	−0.002	0.072***
	0.014	0.02	0.02
Temperature	−0.031**	0.053**	−0.069***
	0.013	0.021	0.017
HDI	−0.002	0.002	−0.001
	0.005	0.007	0.006
Unemployment	−0.004	−0.033**	0.048***
	0.009	0.013	0.014
Observations	490	469	490
Provinces	70	67	70

Notes: Poisson regressions with year and provincial conditional fixed effects. Dependent variable: Casualties. Coefficients and standard errors for year binary variables are omitted for presentation. *Neighbor conflict* and *Muslim pop.* dropped from model due to invariance. To control for population scale, the coefficient for provincial population is fixed to unity using the "exposure" option in STATA. *p > 0.10 **p > 0.05, ***p > 0.01.

Table 15A
Typhoons and the incidence of conflict violence.

	All attacks	Insurgent attacks	Government attacks
	64A	65A	66A
Typhoons	0.534***	0.408***	0.597***
	0.043	0.071	0.054
HDI	−0.006**	−0.005	−0.006*
	0.003	0.005	0.003
Unemployment	0.019***	−0.008	0.032***
	0.006	0.011	0.007
Observations	511	476	511
Provinces	73	68	73

Notes: Poisson regressions with year and provincial conditional fixed effects. Dependent variable: Attacks. Coefficients and standard errors for year binary variables are omitted for presentation. *Neighbor conflict* and *Muslim pop.* dropped from model due to invariance. To control for population scale, the coefficient for provincial population is fixed to unity using the "exposure" option in STATA. *p > 0.10 **p > 0.05, ***p > 0.01.

Table 16A
Typhoons and conflict severity: KIA.

	All KIA	Insurgent KIA	Government KIA
	67A	68A	69A
Typhoons	0.438***	0.553***	0.363***
	0.087	0.128	0.119
HDI	0.015***	0.009	0.022***
	0.005	0.007	0.007
Unemployment	0.012	−0.028**	0.070***
	0.01	0.013	0.015
Observations	497	469	497
Provinces	71	67	71

Notes: Poisson regressions with year and provincial conditional fixed effects. Dependent variable: KIA. Coefficients and standard errors for year binary variables are omitted for presentation. *Neighbor conflict* and *Muslim pop.* dropped from model due to invariance. To control for population scale, the coefficient for provincial population is fixed to unity using the "exposure" option in STATA. *p > 0.10 **p > 0.05, ***p > 0.01.

Table 17A
Typhoons and conflict severity: Casualties.

	All casualties	Insurgent casualties	Government casualties
	70A	71A	72A
Typhoons	0.259***	0.553***	0.077
	0.07	0.124	0.086
HDI	0	0.007	−0.001
	0.005	0.007	0.006
Unemployment	−0.004	−0.033**	0.046***
	0.009	0.013	0.013
Observations	504	469	504
Provinces	72	67	72

Notes: Poisson regressions with year and provincial conditional fixed effects. Dependent variable: Casualties. Coefficients and standard errors for year binary variables are omitted for presentation. *Neighbor conflict* and *Muslim pop.* dropped from model due to invariance. To control for population scale, the coefficient for provincial population is fixed to unity using the "exposure" option in STATA. *p > 0.10 **p > 0.05, ***p > 0.01.

Table 18A
Rainfed rice and the incidence of conflict violence.

	All Attacks	Insurgent attacks	Government attacks
	73A	74A	75A
Rainfed rice	−0.150***	−0.118***	−0.168***
	0.01	0.017	0.012
HDI	−0.019***	−0.016***	−0.020***
	0.003	0.005	0.003
Unemployment	0.007	−0.020*	0.019***
	0.006	0.011	0.007
Observations	504	469	504
Provinces	72	67	72

Notes: Poisson regressions with year and provincial conditional fixed effects. Dependent variable: Attacks. Coefficients and standard errors for year binary variables are omitted for presentation. *Neighbor conflict* and *Muslim pop.* dropped from model due to invariance. To control for population scale, the coefficient for provincial population is fixed to unity using the "exposure" option in STATA. *p > 0.10 **p > 0.05, ***p > 0.01.

Table 19A
Rainfed rice and conflict severity: KIA.

	All KIA	Insurgent KIA	Government KIA
	76A	77A	78A
Rainfed rice	−0.053***	−0.075***	−0.025
	0.018	0.024	0.026
HDI	0.009*	0	0.019**
	0.005	0.007	0.008
Unemployment	0.008	−0.036***	0.072***
	0.01	0.014	0.016
Observations	490	462	490
Provinces	70	66	70

Notes: Poisson regressions with year and provincial conditional fixed effects. Dependent variable: KIA. Coefficients and standard errors for year binary variables are omitted for presentation. *Neighbor conflict* and *Muslim pop.* dropped from model due to invariance. To control for population scale, the coefficient for provincial population is fixed to unity using the "exposure" option in STATA. *p > 0.10 **p > 0.05, ***p > 0.01.

Table 20A
Rainfed rice and conflict severity: Casualties.

	All casualties	Insurgent casualties	Government casualties
	79A	80A	81A
Rainfed rice	−0.110***	−0.059**	−0.097***
	(0.016)	(0.023)	(0.022)
HDI	−0.008*	0	−0.006
	(0.005)	(0.007)	(0.006)
Unemployment	−0.017*	−0.039***	0.035***
	(0.009)	(0.013)	(0.014)
Observations	497	462	497
Provinces	71	66	71

Notes: Poisson regressions with year and provincial conditional fixed effects. Dependent variable: Casualties. Coefficients and standard errors for year binary variables are omitted for presentation. *Neighbor conflict* and *Muslim pop.* dropped from model due to invariance. To control for population scale, the coefficient for provincial population is fixed to unity using the "exposure" option in STATA. *p > 0.10 **p > 0.05, ***p > 0.01.

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